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OPTICAL PATTERN RECOGNITION

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13. ABSTRACT *(Maximum 200 words)*
This study provides a basic understanding of the fundamentals of optical pattern recognition systems. An emphasis on the capabilities and limitations of such systems is presented. Areas in need of further development are highlighted. Pattern recognition using optical systems can be performed based on either correlator or non-correlator systems. Recognition can be achieved by using linear processing techniques such as wavelet transforms or nonlinear processing using morphological operations or neural networks. The fundamentals of pattern recognition are presented, specifically, Fourier transformation using lenses, and the basic optical correlator architecture. Both the 4-f in-line and joint-transform correlators are described with an emphasis on the advantages and limitations of each. Morphological processors, neural-network and wavelet transform systems are introduced along with their optical implementations. A brief overview of the optical components involved in the design and fabrication of optical pattern recognition systems is discussed. Spatial filter designs used in optical correlator systems are reviewed with particular emphasis on distortion-invariant applications. Discussion of system performance criteria, and a comparison between some of the systems, are included.

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CHAPTER 1
INTRODUCTION

Pattern recognition is a field of great interest with a wide range of applications. It involves systems that are capable of recognizing patterns. These patterns can be as simple as an alphabet character or a complex image such as a human face. The application of machine vision to sorting products on industrial assembly lines; recognizing fingerprints; and, on the battlefield, recognizing mine fields or track enemy tanks and airplanes are all of great importance. Pattern recognition is an intriguing problem that has been of interest to researchers over the last three decades. Recognition needs to be performed at high speed with a high confidence level. Discrimination between similar objects is very crucial. The object to be recognized can be distorted and/or corrupted by noise. It has been realized for a long time that recognizing objects with arbitrary aspect projection, scale, and rotation is a computationally intensive problem.

Optics with its inherent parallelism and speed presents the proper medium for solving problems with intensive computational needs. Optical systems seem to be a natural way for implementing machine vision applications since the patterns to be recognized are usually present in an optical format such as an image. Optical correlation techniques via the lens Fourier transformation property are the backbone of optical pattern recognition systems. The capability of performing signal processing operations such as Fourier transformation, correlation and convolution of two-dimensional signals in parallel has always been the strength of optical systems. These properties have always provided optical information processing systems an advantage over electronic systems which are in general sequential in nature. The new surge of highly developed devices (i.e., lasers, detector arrays and spatial light modulators (SLMs), filter designs and recent developments in neural networks (NNs) and wavelet transforms (WTs)) have greatly made optics a viable contender in pattern recognition and computing applications.

This study provides a vehicle for understanding the basic fundamentals of optical pattern recognition systems. An emphasis on the capabilities and limitations of such systems is presented. Areas in need of further development are highlighted. The applications of such systems to specific military, industrial and commercial uses will be briefly mentioned. *Therefore, this document should primarily be used as a basis for understanding the operation, characteristics and limitations of these systems.*

Optical pattern recognition is a major branch of optical processing and computing. It can be categorized based on a variety of factors (Figure 1). It can be categorized as coherent or incoherent depending on the source of illumination used. Optical data processing can be performed either in the space domain or in the frequency domain. This data processing can either be linear or nonlinear in nature. Pattern recognition in general can be performed by comparing the input pattern to a template of

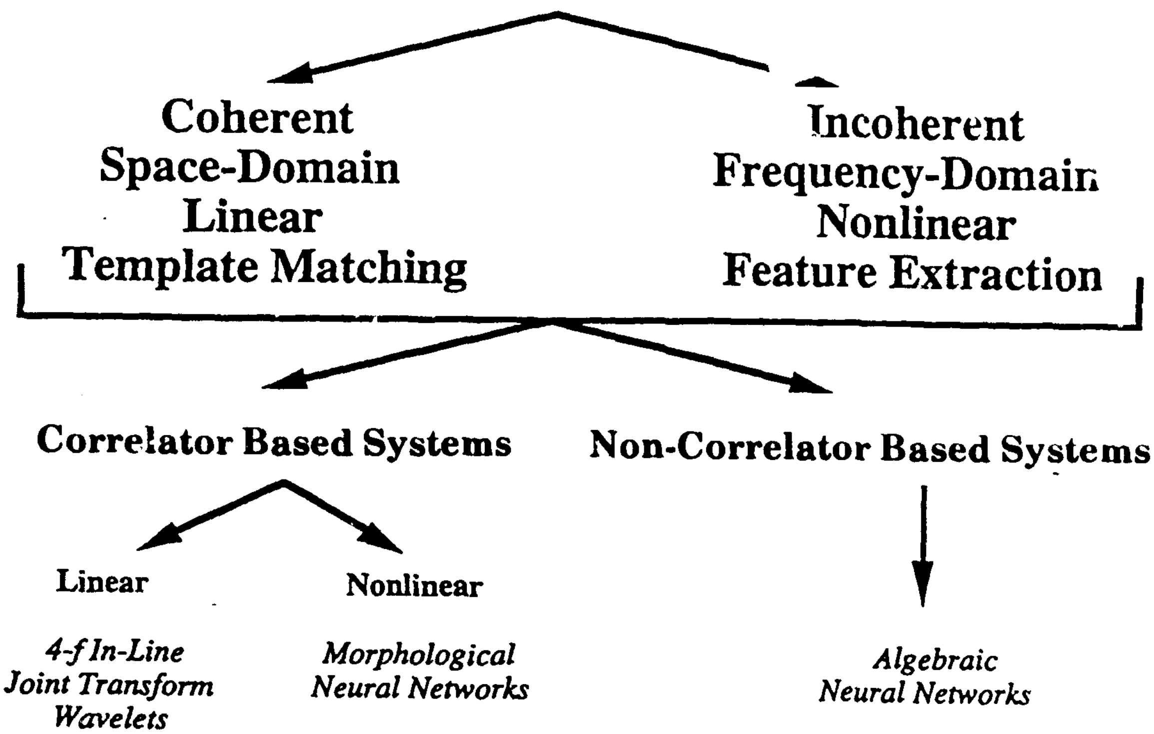


FIGURE 1. OPTICAL PATTERN RECOGNITION SYSTEMS

stored reference patterns, *template-matching*, or it can be done by extracting certain features from the pattern and making a decision based on that, *feature-extraction*.

Pattern recognition using optical systems can be performed based on either correlator or non-correlator systems. Correlator-based systems are much more widely used because of the capability of optical systems to perform such operations on two-dimensional images in parallel. There are two basic architectures of optical correlators: 4-f in-line and joint-transform. Pattern recognition can be performed directly using correlations and thresholding. Also, recognition can be achieved by using linear processing techniques such as WTs or nonlinear processing using morphological operations or NNs. Non-correlator systems are based on algebraic processors such as vector-matrix multipliers.

Chapter 2 presents definitions for some of the basic optical pattern recognition terminology. Pattern recognition systems are introduced in Chapter 3. We start with the fundamentals of pattern recognition, Fourier transformation using lenses, and the basic optical correlator architecture. Both the 4-f in-line and joint-transform correlators are described with an emphasis on the advantages and limitations of each. Morphological processors are introduced along with their optical implementations. NN and WT systems are considered with emphasis on their optical implementations. Chapter 4 presents a brief overview of the optical components involved in the design and fabrication of optical pattern

recognition systems. SLM fundamentals and comparison between the major available devices are given in Chapter 5. Spatial filter designs, used in optical correlator systems, are reviewed in Chapter 6 with particular emphasis on distortion-invariant applications. Chapter 7 is a preliminary discussion of system performance criteria and a comparison between some of the systems discussed in Chapter 3. Chapter 8 summarizes the discussion and provides guidelines for future research and development. An extensive list of references is also provided.

CHAPTER 2
OPTICAL PATTERN RECOGNITION DEFINITIONS

COHERENT

Coherent optical processors are based on using coherent light illumination. The system is analyzed using Fourier optics. The system is linear space-invariant in terms of the amplitude of the electric field. The output is the convolution of the input function with the impulse response of the system.

INCOHERENT

Incoherent optical processors are based on the use of partially coherent light for illumination. This system is linear in intensity. The output intensity of the system is the convolution of the input intensity with the modules square of the impulse response. Incoherent processors do not suffer from coherent artifact noise. Also, the input does not need to be displayed on a SLM, which eliminates the need for incoherent-to-coherent converters. Color image processing can be done using incoherent systems.

SPACE- AND FREQUENCY-DOMAIN PROCESSING

Data manipulation in both coherent and incoherent processors can be done in either the spatial domain (object space) or frequency domain (Fourier or other transform space). In the object space processing case, object and reference are both processed without transforming. In the frequency domain processing case, transforms of the object and reference are computed first, then processed.

SPACE-DOMAIN PROCESSORS

There are a number of techniques that are used in space domain optical processors; we describe a few of these techniques here.

Shadow Casting

In this technique the object and reference are imposed on top of each other to perform the desired operation. In the case of correlators, the object and the reference patterns are scanned either optically (by using a collimated beam followed by a ground glass) or mechanically (by moving one of the patterns with respect to the other).

Algebraic

Many optical processing operations can be achieved using linear algebra manipulations. These can be implemented by using vector-matrix and matrix-matrix multiplication type operations. Vector-matrix multiplication is performed by expanding each element of the input vector and casting each on a row of the matrix which is displayed on either a fixed mask or a dynamic SLM. The output from each column is focused to form an element of the output vector.

FREQUENCY-DOMAIN COHERENT PROCESSORS

Frequency-domain processing in a coherent system is mainly dominated by correlators.

Correlators

Optical coherent correlators are the most widely used systems in pattern recognition. Correlation is achieved in frequency domain processing by superimposing the Fourier transform (FT) of the input function and the complex conjugate of the FT of the reference function on each other (to multiply the two functions). The inverse FT of the product results in the correlation of the two functions. The FT of the reference function is referred to as the filter. There are a wide variety of filter designs. We will describe filter designs later in this document. The following is a discussion of some of the systems and applications based on coherent correlators.

4-f In-Line Correlator System

This is the basic building block for optical data processing systems. The input function is placed a distance F, focal length, in front of a Fourier transforming lens and illuminated with collimated coherent light. The filter is placed in the back focal plane of this Fourier transforming lens. The back focal plane of the lens is referred to as the Fourier plane or the frequency domain. Another Fourier transforming lens is placed a distance F behind the filter plane and in the back focal plane of this lens is the output plane. The first lens performs the FT and the second lens performs the inverse Fourier transform (IFT) operation. The output will depend on the filter pattern. If it is the transform of the reference function, the output will be the convolution of the input function and the reference function. If the filter is the complex conjugate of the reference function, the output will be the correlation of the input and reference function.

Joint-Transform Correlator

In this system both input and reference functions are placed in the input plane, displayed on the same SLM, in the front focal plane of a FT lens. FT of both functions is formed in the back-focal plane of the lens. The pattern resulting from the interference of both transforms is detected and displayed on another SLM. A FT of the interference pattern is produced by another FT lens and the correlation of the

two functions will be formed in the back focal plane of this lens. Also in this system, the convolution of the two functions will be present at the output plane. In both the in-line and the joint-transform correlators, the convolution and correlation are displayed at different locations in the output plane, so they can be detected separately.

Wavelets

WTs are multiple correlations of the signal with a wavelet function which has a variable scale. Wavelets can provide position and scale invariant detection and classification of images with low signal-to-noise ratios. Optical correlators can be used to implement WTs in parallel. Wavelets are used in time-frequency and multiresolution analysis. There are a wide range of wavelet functions that can result in a wealth of applications.

NONLINEAR PROCESSORS

Morphological Processors

Optical morphological processors are based on specific mathematical operations performed on an image. There are two main operations: dilation and erosion, on which morphological operations are based. Using these two basic operations, opening, closing, segmentation, skeletonization, noise suppression, edge detection and pattern recognition are realized. Optically these operations are implemented using space- (shadow-casting and defocused imaging) and frequency-domain correlators. The correlation is performed between the input image and a structuring element. In pattern recognition the hit-or-miss transform (HMT) is used. The HMT detects specific features from the input image and leaves a single spot in its place with all other features suppressed. Morphological systems are also used very efficiently in preprocessing systems for image enhancement, the output of which can be processed using other pattern recognition systems, such as an optical correlator.

Neural Networks

Artificial NNs are nonlinear systems. They are a distributed system of interconnected nodes and nonlinear processing elements, mimicking the brain. The high connectivity of NNs provides a high capability of feature extraction and classification. The interconnections between the nodes are on the order of N^2, where N is the number of nodes. This high interconnection density makes it extremely difficult to hardwire electronically. The inherent parallelism of optics and high connectivity makes it the natural choice for such an application. The challenging part of the system is the non linearity needed for implementing the neuron. This can be achieved using optoelectronic devices. Artificial NNs can be implemented either using algebraic (matrix-vector multiplier) or correlator based systems. Also, depending on either recording the interconnection weights off- or in-line, non-adaptive and adaptive NNs, respectively, can be realized.

CHAPTER 3

OPTICAL PATTERN RECOGNITION SYSTEMS

Optics with its parallelism attracted much attention during the development of pattern recognition systems. Patterns to be recognized usually are in an optical format, i.e., an image. This format lends itself to the optical domain and it seems more natural to be processed optically. In the last three decades since the invention of the laser, a great deal of research has been directed towards developing optical pattern recognition systems. Coherent optical Fourier processors capable of performing vital mathematical operations such as Fourier transformation, correlation and convolution of two-dimensional signals became the center of attention for such applications. The introduction of the Vander Lugt filter[1] was a necessary breakthrough to initiate such efforts. Since then, many system architectures and filter designs have been introduced. A major problem hindering the development of such systems is the interface device limitations--SLMs in particular. Recently, technological advances in such devices have made pattern recognition systems more feasible.

This chapter introduces the fundamentals of pattern recognition, then turns to specific systems, both correlator- and non-correlator based.

PATTERN RECOGNITION FUNDAMENTALS

Pattern recognition here is meant in the general sense, i.e., character, image, speech or signal recognition. The fundamental objective of pattern recognition is the classification of the input pattern. Pattern recognition in general uses two broad techniques: *template matching* and *feature extraction*.[2-4] Template matching is based on comparing an input pattern to a template of all possible patterns. This comparison can be made by performing correlation using space or frequency domain techniques. In feature extraction, the system is considered as a two-stage device. The first stage is feature extraction and the second stage is classification. Features are defined as measurements taken on the pattern. A set of measured features is supplied to the classifier. The classifier's task is to map these input features onto a classification state.

OPTICAL CORRELATORS

Correlation is an operation to compare two patterns. Consider two functions f(x) and g(x); the correlation is defined using the following mathematical operation:

$$c(x) = \int_{-\infty}^{\infty} f(\beta) g^{*}(\beta - x)\, d\beta, \tag{1}$$

FT system) on FG'. This results in the correlation of f(x,y) and g(x,y) which is represented as $f \ast g$, where $\ast$ denotes the correlation operation. The functions f(x,y) and G'(u,v) can be recorded on a photographic film or written on a SLM. The complex conjugate of the FT of g(x,y), g'(u,v), can be generated optically[6] or numerically by a computer.

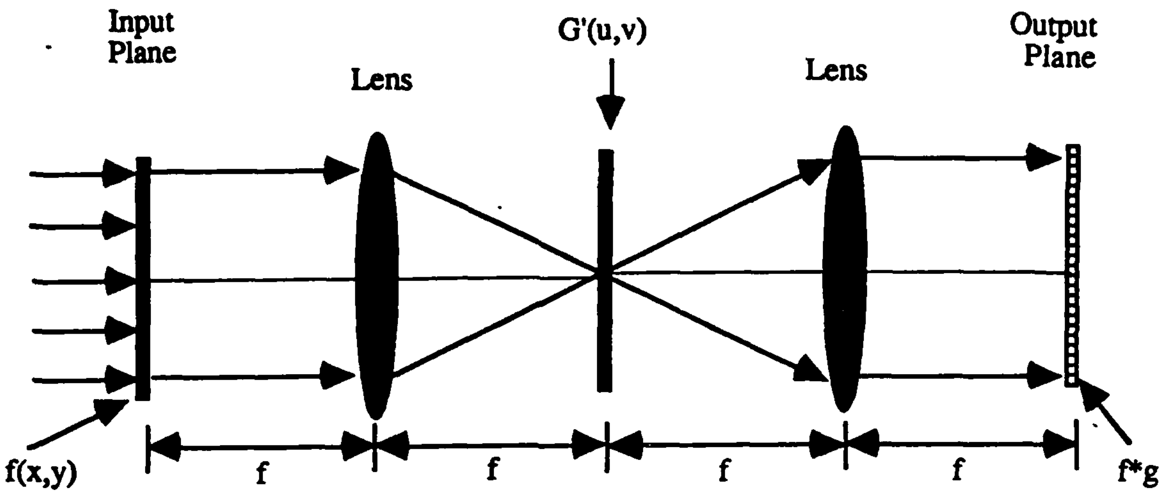


FIGURE 3. OPTICAL CORRELATOR SYSTEM, CORRELATING FUNCTIONS f(x,y) AND g(x,y)

The correlation is performed in parallel in two dimensions. As in the case of Fourier transformation, the speed of the correlation operation is limited only by the time required for the light to travel from the input to the output plane. This system is referred to as the 4-f in-line correlator. It is the basic building block of most coherent optical signal processing systems. In this system if we replace G' by G the output will be convolution instead of correlation. These operations are analog in nature so the accuracy will be limited by the interface devices both in reading and writing the different functions.

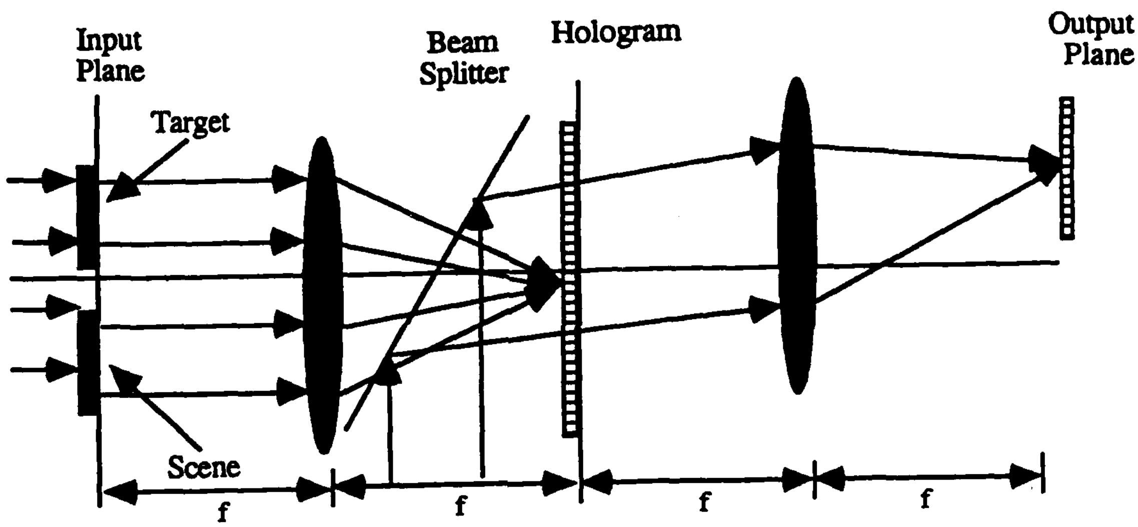
The function G'(u,v) is placed in the frequency domain and it is referred to as the filter function. A large body of literature exists regarding these filters and their design. Filter design will be discussed later in this document.

This system is translation invariant. Translating the object in the input plane does not affect the position of its FT. Its transform remains centered with some phase change. The correlation spot tracks the object indicating its exact position in the scene. The classical matched filter introduced by Vander Lugt is holographically recorded.[1] Placing the filter in the Fourier plane is very critical; it allows only a few microns of tolerance perpendicular to the optic axis and tens of microns along the optic axis.[6,7] This is a severe requirement on such systems and places a great emphasis on filter positioning. Changing the scale or the orientation of the input object will reflect directly on the scale and rotation of its FT. If this takes place in the correlator system, the correlation peak becomes very small and the system fails to recognize the object. This sensitivity to scale and rotation changes is considered one of the major problems facing such correlator systems. A number of techniques have been proposed to design filters which can accommodate the in-plane scale and rotation changes.[8-13] Some of these techniques will be discussed later.

JOINT TRANSFORM CORRELATOR (JTC)

The positioning of the filter in the frequency plane (focal plane of the lens) presents a severe restriction especially for high data inputs. The JTC was proposed as an improvement to the 4-f in-line correlator for objects of great similarity and, also, it relaxes the filter positioning problem mentioned above.[14-17]

In this correlator architecture both target and scene patterns are presented at the input plane simultaneously. Patterns are placed in the front focal plane of a Fourier transforming lens and illuminated by a coherent plane wave. Electric field distribution of FTs of both patterns are added to produce an interference pattern at the back focal plane of the lens, as shown in Figure 4. This interference pattern is recorded on a photographic plate as a hologram. The processed hologram is illuminated by a plane wave and the correlation of the target with the scene is produced at the back focal plane of the lens.



(Both recording and reading are superimposed.)
FIGURE 4. JOINT TRANSFORM CORRELATOR

As in the case of 4-f in-line correlators using a holographic filter, the output plane contains convolution, correlation and distorted images of the two functions. These are located in different positions in the output plane.

The JTC system is advantageous in two respects. First, provided that the hologram is to be replaced by a real-time optoelectronic device such as an SLM or a detector and SLM combination, its parallelism is achieved.[18] The input and filter patterns can be displayed on the same SLM or two different SLMs. This makes the system operate in near real-time and the reference filter need not be recorded in advance. Second, the problem in positioning the filter in the Fourier plane is also alleviated since the FT of the input and filter patterns are formed by the same lens.

SHADOW-CASTING CORRELATOR

Shadow-casting correlators do not operate on the basis of the FT product. They operate on the patterns directly in the spatial domain.[19, 20] This technique is based on casting the shadow of one pattern on top of the other and scanning them with respect to each other, either optically or mechanically, and computing the area of overlap. It literally implements the correlation operation by scanning one of the functions over the other. This particular system uses incoherent light illumination to avoid the interference and diffraction effects of the coherent processor. The system is based on geometrical optics imaging analysis and ignores diffraction completely. A possible system architecture is shown in Figure 5. In this system an incoherent extended light source is used for illumination.

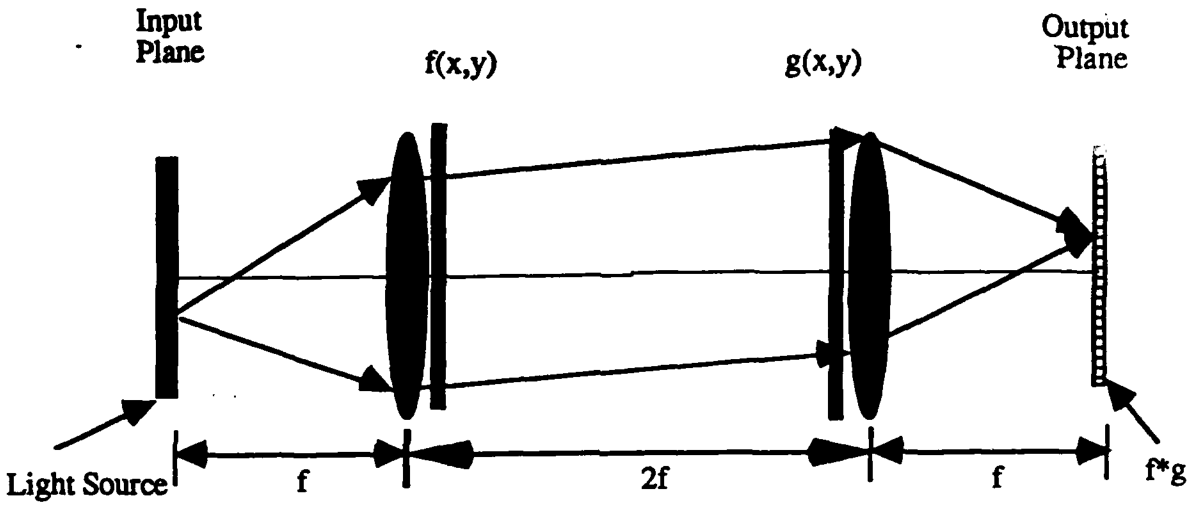


FIGURE 5. SHADOW-CASTING CORRELATOR

If we consider one point on the two-dimensional light source, the first lens expands and collimates the beam. The collimated beam passes through object f(x,y) and casts it on g(x,y). The second lens focuses the light on the output plane. The value of the output is the integration of the overlap of functions f(x,y) and g(x,y). Another point on the light source casts a different projection of f(x,y) on g(x,y). The large number of different points on the light source cast a large number of different projections of f(x,y) on g(x,y). The projection of such patterns is the equivalent of scanning f(x,y) on g(x,y) and measuring the overlap area of each of these projections. This in turn results in the correlation of the two functions.

OPTICAL MORPHOLOGICAL PROCESSORS

These processors implement morphological operations. Mathematical morphology is a set operational method in image analysis.[21-23] A number of digital, incoherent, and coherent optical system implementations have been proposed.[24-27] This chapter introduces the basic morphological operations, their optical implementations and their application in pattern recognition and classification.

Morphology Fundamentals

Let us consider the most basic and fundamental operations in mathematical morphology, namely *dilation* and *erosion*. All other operations in morphology are based on dilation and erosion. Consider an image X and a structuring element B. Dilation is defined as

$$X \Theta B = \{a : B_a \subseteq X\}, \tag{3}$$

where θ denotes dilation, B_a is set B shifted by "a", and $\subseteq$ denotes a subset. Similarly erosion is defined as

$$X \oplus B = \{a : B_a \cap X \neq 0\}, \tag{4}$$

where $\oplus$ denotes erosion and $\cap$ is the intersection or AND operation. An erosion followed by a dilation is an *opening*, and a dilation followed by an erosion is a *closing*. Physically, erosion shrinks the image and dilation expands it. Opening smoothes the contours of the image from the inside and suppresses the sharp capes and cuts the sharp isthmuses of the image, while closing smoothes the contours of the image from the outside and fills up its thin gulfs and small holes. An example of these operations is shown in Figure 6 along with the image X and structuring element B.

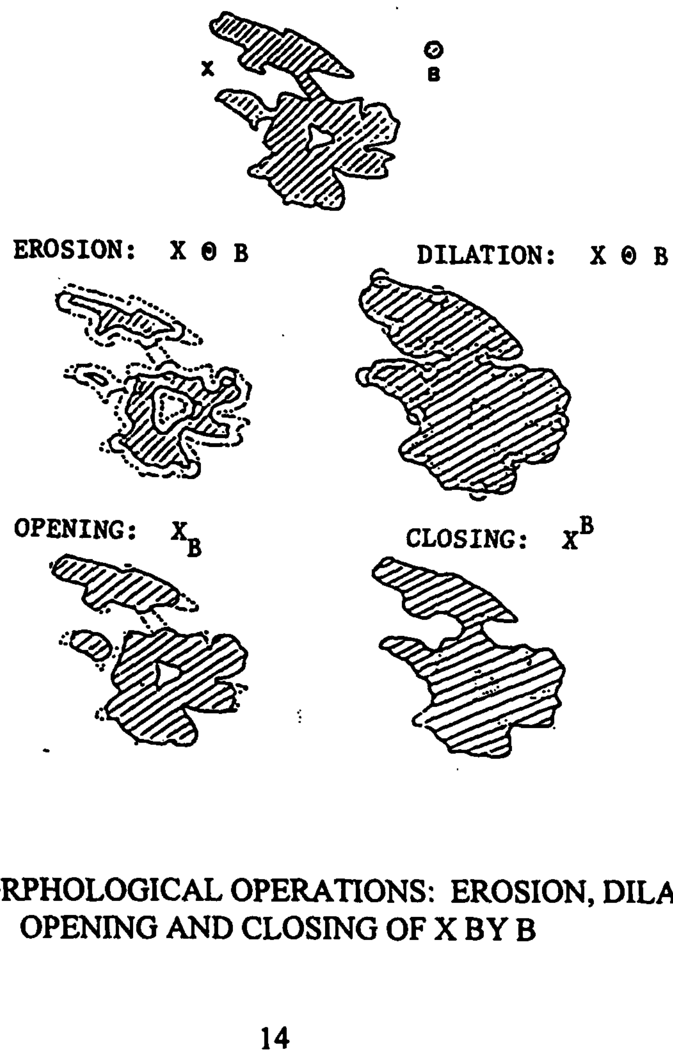


FIGURE 6. MORPHOLOGICAL OPERATIONS: EROSION, DILATION, OPENING AND CLOSING OF X BY B

These basic morphological techniques are used to perform a number of image analysis operations such as edge detection, noise suppression, segmentation, skeletonization and hit-or-miss transformation. Morphology is used for both binary and gray-level images. It has many applications for image analysis in different fields, from biology and petrology to different industrial applications.

Morphology Applications

Morphology has many applications in image analysis and enhancement. Many image processing operations can be achieved by a sequence of the basic fundamental morphology operations. Noise suppression can be achieved by an opening followed by a closing version.

The application of interest in this study is pattern recognition. This is performed in morphology through the HMT. HMT detects a particular feature from an input image and leaves a single pixel in its place, suppressing the rest of the image. HMT is defined by two structuring elements. The first represents the desired feature and the second is its complement. Consider an image X, and its complement X^c, a foreground structuring element B, and a background structuring element D, then the HMT is defined as

$$X \otimes (B,D) = (X \Theta B) \cap (X^c \Theta D) \, . \tag{5}$$

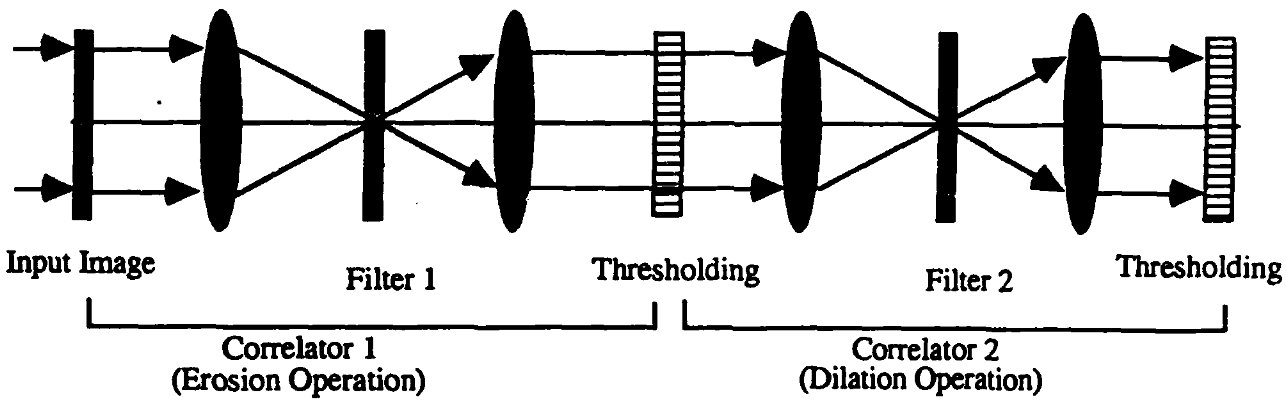
The first erosion of X by B gives an output peak wherever the foreground object B is present in X. The second erosion of X^c by D gives a peak wherever object D is present in the complement of image X. The intersection $\cap$ (AND) of the two erosions creates an output only if the foreground and background objects are both present. Object B is the feature we desire to extract from the image.

OPTICAL IMPLEMENTATION

Optical implementation of morphological operations can be realized by many different systems. Symbolic substitution based systems are introduced to perform both dilation and erosion using a structuring element as the basis for the substitution.[18, 28, 29] Implementing the basic morphological operations optically can also be achieved by using optical correlators.[17,19, 30, 31] The existing implementations are mainly binary. Gray-level implementations have also been proposed.[32, 33]

Both erosion and dilation can be performed by correlating the image with the structuring element and using the proper threshold. Morphological operations are nonlinear because of this thresholding operation. They can be used in either image classification or image recognition and detection.

Consider the optical correlator shown in Figure 3. It can be used for the dilation and erosion operations. In the filter plane the transform of the structuring element is placed while the image is introduced in the input plane. At the output plane, the correlation of the image with the structuring element will result. Assume that the filter of the structuring element B has N pixels. In a binary implementation if we apply a high threshold $T_H = N$ an erosion results and if a low threshold $T_L = 1$ is used a dilation results.[19] Using thresholding levels between T_L and T_H produces a rank-order filter operation. A system which can implement these higher-order morphological operations must be iterative to cascade the erosion and dilation operations. Such a system is shown in Figure 7.



(Filters 1 and 2 are the FT of the proper structuring element.)
FIGURE 7. OPTICAL SYSTEM FOR IMPLEMENTING OPENING OPERATION

Figure 7 shows an example of how to implement a morphological operation. The system can also be designed using only one correlator stage and performing the interactive process through feedback loops.

Morphological processors can play an important role in the preprocessing of images since they can be used in image enhancement and noise reduction. Using these processors for image recognition and classification can be done using HMT.

OPTICAL NEURAL NETWORKS

NNs are systems that mimic the brain. The brain is very powerful in quickly recognizing images. NNs are based on a simple nonlinear processing element (neuron). Neurons are distributed and interconnected. NNs achieve their computation through the evolution of the system.[34-38] A model for the neuron is shown in Figure 8.

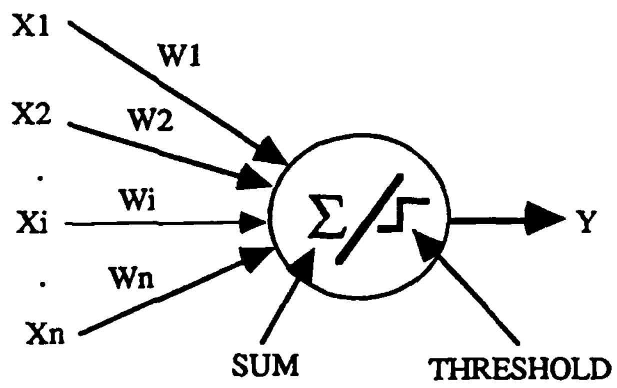


FIGURE 8. NEURON MODEL

In this neuron model, which is considered as tl.. processing element in the NN, the relation between the output Y and the excitations x_i and weights w_i is

$$y = f_h\left[\sum_{i=1}^{n} w_i x_i\right], \tag{6}$$

where f_h is a step function (known as the heaviside function) given by

$$f_h(x) = \begin{cases} 1 & x > 0 \\ 0 & x \le 0 \end{cases}. \tag{7}$$

The output of the neuron will be on if the sum of the weighted input values exceeds a certain threshold; otherwise, the neuron will be off. The thresholding function constitutes the nonlinear nature of these neurons. The model neuron is known as the "*perceptron*." Each set of nodes is comprised in a neural layer. Several neural layers can be cascaded to form a multilayer system.

The perceptron can learn to classify different patterns from one another by adjusting its weights. A single layer perceptron can be used as a linear classifier; i.e., it can classify patterns that can be separated in the two-dimensional Euclidean feature space by a straight line.

An improvement on the single layer perceptrons to perform more complex pattern classifications is achieved by two steps. First the non-linearity must be changed to become either linear or sigmoidal (Figure 9).

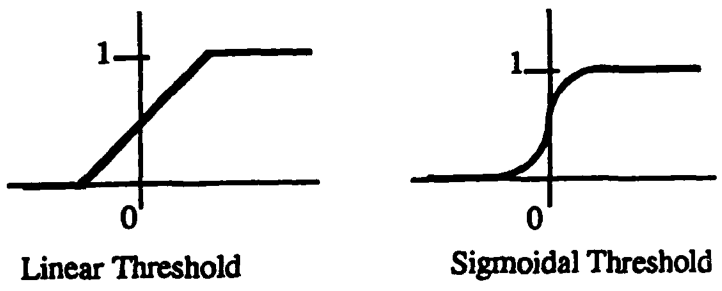


FIGURE 9. LINEAR AND SIGMOIDAL THRESHOLD

The second step is the use of multilayer NNs. The basic model is now made of an input layer, an output layer and a middle layer which is not connected directly to the input or the output. The middle layer is called the *hidden* layer. The new model is shown in Figure 10. The learning algorithm for this model is the famous back propagation rule.[39,40]

The three-layer NN is capable of the classification of any pattern regardless of how complex the shape. This is referred to as the *Kolomogrov* theorem.[30] A summary of NNs classification abilities is shown in Figure 11. Using sigmoidal thresholding will make the classification regions smooth. The complexity of the classification problem will affect the number of nodes in each of the network layers.

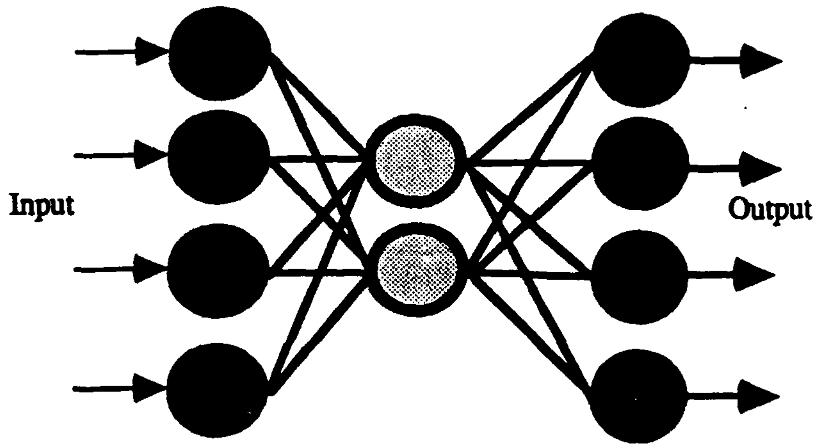


FIGURE 10. THE MULTILAYER NEURAL NETWORK

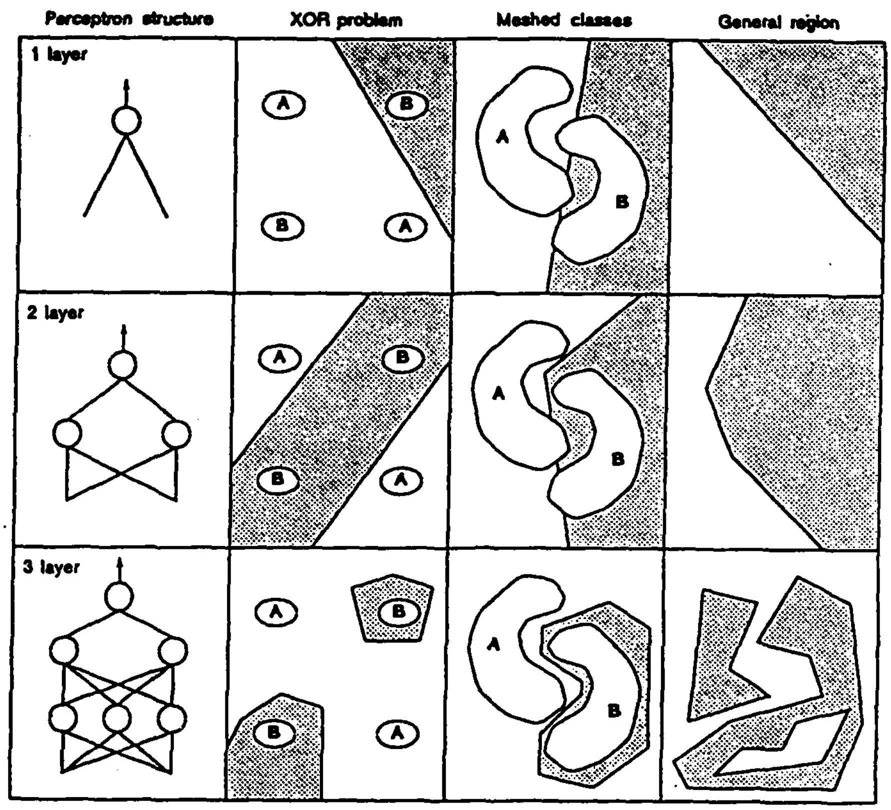


FIGURE 11. NEURAL NETWORKS AND THEIR CORRESPONDING DECISION REGIONS

OPTICAL IMPLEMENTATIONS OF NEURAL NETWORKS

NNs are highly interconnected. Optics with its natural parallelism provides a suitable means of implementing neural networks. The wide-bandwidth high-volume interconnection of optics allows a large number of neurons to be connected with each other. This immense interconnectivity is due to the fact that light beams can cross each other with no effect. A large number of systems have been proposed to implement NNs optically.[41-45] Implementing NNs optically is done using linear algebraic processors[33, 34] and optical correlators.[35-37, 46, 47] Thresholding is achieved either through optically addressed spatial light modulators or through optoelectronic devices (detector arrays). Application in associative memory, image classification, and recognition are typical for the NN.

LINEAR ALGEBRAIC PROCESSOR-BASED NEURAL NETWORKS

The direct implementation of NNs is by using vector-matrix multipliers. The input data can be written as a vector and the interconnection weights as a matrix. Thresholding can be done using optoelectronic devices. Figure 12 shows a typical implementation of a NN using an optical vector-matrix multiplier.

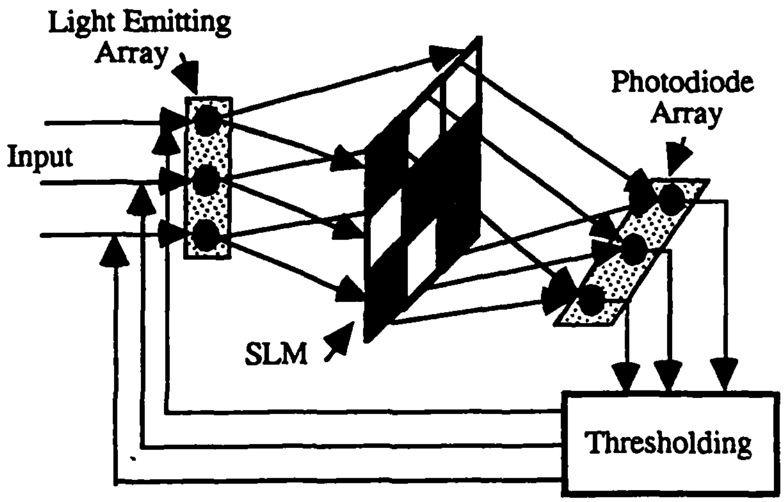


FIGURE 12. OPTICAL NEURAL NETWORK USING VECTOR MATRIX MULTIPLIER

In this system the input to the network modulates the intensity of the light emitting diodes (LED) (representing the neurons). Light from each LED is spread horizontally and passes through a row of the weight matrix displayed on the SLM. The light emerging from the SLM is the product of the input with the corresponding weight. Light emerging from each column of the matrix is focused on a photodiode which corresponds to a summing operation. As the output vector emerges it is thresholded. The output can be fed back if more iterations are desired. The time required for the operation is independent of the size of the network since all the multiplications and summations are done in parallel.

CORRELATOR- BASED NEURAL NETWORKS

The main operation of NNs is thresholding the inner product of the input with the weights. The inner product can be considered as a correlation. Moreover, correlation is an invariant inner product. Optical correlator systems demonstrate the massive interconnection desired by NNs. Optical correlators are used to construct auto associative memories and other NN configurations.[36, 48, 49]

A proposed system for associative memory applications is shown in Figure 13.[49] In this system the input image is split by the beam splitter in two copies. One is recorded on the thresholding device (it can be an SLM) and the other copy is projected on the hologram H1. This hologram contains the images to be recognized by the system. The input pattern passes through the hologram, which correlates the input image with the stored patterns. The output from the hologram is focused and passed through a pinhole which is subsequently collimated and passed through the second hologram H2. This hologram is similar to the first. The collimated beam reconstructs the image that most likely corresponds to the input image. The hologram output is imaged on the thresholding device which passes to its other surface the brightest image. The enhanced image displayed on the other surface of the thresholding device is reflected off its surface and passed through hologram H1 for a second iteration. The enhanced image continues to be iterated until the output of the system settles with no further changes in the output. The speed that the system relaxes is limited by that of the thresholding device. This system is capable of recovering an image when only a very small proportion of the original image is presented.

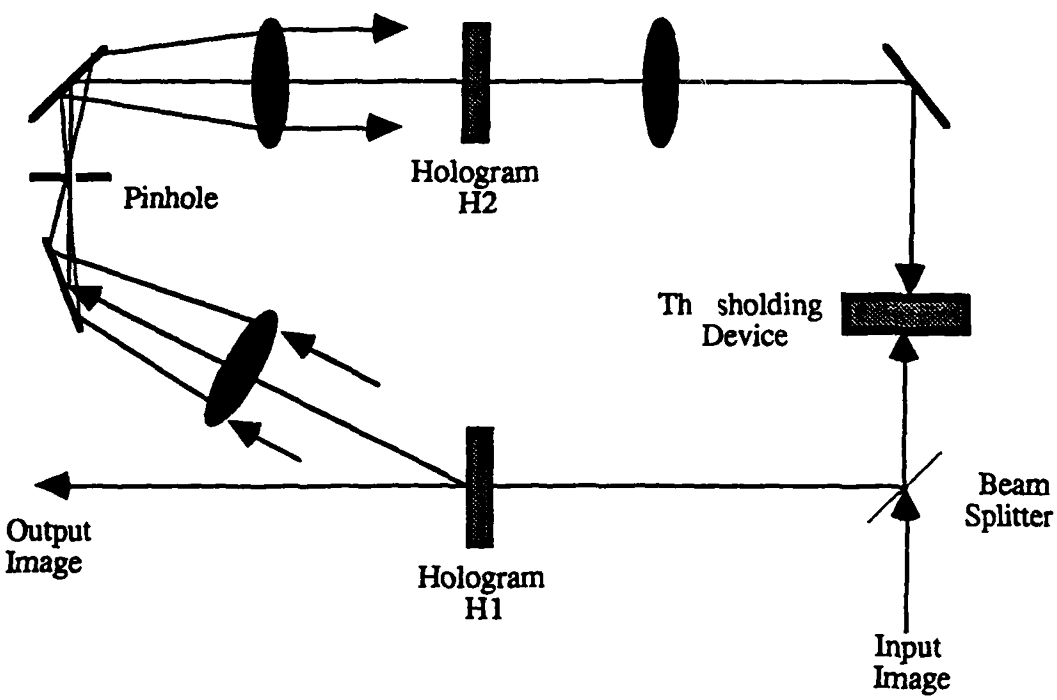


FIGURE 13. A HOLOGRAPHIC PATTERN RECOGNITION NEURAL NETWORK

OPTICAL WAVELET TRANSFORMS

Image processing, in general, is based on either space or frequency domain analysis. These analyses extensively use Fourier methods. In Fourier analysis the signal is decomposed into linear combinations of elementary functions. The FT of the function g(x) is defined as

$$G(f_x) = \int_{-\infty}^{\infty} g(x)\, e^{-j2\pi f_x x}\, dx. \tag{8}$$

The FT integrates the function g(x) over space extending from -∞ to ∞. This makes FT more suitable for stationary signals (signals that do not change in space). In many applications signals need to be analyzed in both the space and frequency domains. Ambiguity and Wigner distribution functions are two examples of time-frequency analysis. The Ambiguity function[50] is used for time-Doppler shift signal representation, and the Wigner distribution function[51-53] is a time-frequency representation of the signal.

The WT is a new basis for representing and analyzing functions in a scale-translation domain.[54,55] WT is efficient in time-dependent frequency analysis of short transient signals. The basic function of the WT, called wavelets [$h_{ab}(x)$], is generated by dilation and translation of a so-called mother wavelet h(x). The wavelets are defined in terms of the mother wavelet by

$$h_{ab}(x) = \frac{1}{\sqrt{a}} h\left(\frac{x-b}{a}\right), \tag{9}$$

where a > 0 is the dilation factor and b is the translation factor. The WT of a function g(x) is defined as

$$W_s(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} h^*\left(\frac{x-b}{a}\right) g(x)\, dx. \tag{10}$$

The function $W_s(a,b)$ can be considered a function of the space shift "b" for each fixed scale "a" that displays g(x) at various levels of resolution. The integral in Equation (10) is a correlation between the signal g(x) and a dilated wavelet. As the dilation factor approaches zero, the wavelet $h_{ab}(x)$ becomes more concentrated about x=b. $W_s(a,b)$ then displays the small-scale high-frequency features of g(x). The larger the dilation factor "a" becomes, the coarser low-frequency features are displayed. In the spatial-frequency domain, the wavelet is expressed as

$$\begin{aligned} H_{ab}(f_x) &= \int_{-\infty}^{\infty} h_{ab}(x) e^{-j2\pi f_x x}\, dx \\ &= \sqrt{a}\, e^{-j2\pi f_x b}\, H(af_x) \end{aligned} \tag{11}$$

where $H(f_x)$ is the FT of h(x). From Equation (11) a dilation x/a in time is equivalent to a compression "af_x" in the spatial-frequency domain, and a shift b is equivalent to a phase shift $\exp(-j2\pi f_x b)$. From Equations (10) and (11) we can get

$$W_s(a,b) = \sqrt{a} \int_{-\infty}^{\infty} H^*(af_x) e^{-j2\pi f_x b}\, G(f_x)\, df_x. \tag{12}$$

There are a number of well-known wavelet functions such as Morlet's,[56] Haar's,[57] Daubechies's,[58] the Mexican-hat[59] and Meyer's.[60]

OPTICAL IMPLEMENTATION OF WAVELET TRANSFORMS

The WT can be implemented optically by a variety of techniques.[61] The WT as defined by Equation (11) is the corr``tion of the signal g(x) with the wavelet h(x), translated by factor "b", and dilated by factor "a". This correlation can be implemented directly using an optical correlator. Another way of implementing the WT is by using Equation (12). The technique uses the FT of the wavelet $h_{ab}(x)$ as the filter to be placed in the FT plane in a coherent optical processor. The WT filter is the FT of the dilated h(x/a) but without any translation. According to Equation (12) the coordinate in the correlation plane is the continuous translation factor b.[62] This method can be implemented by using the system shown in Figure 14.

The optical WT processor shown in Figure 14 is based on a two-dimensional optical multichannel correlator to perform a one dimensional WT. The input signal g(x) is displayed on an SLM, such as an acousto-optic modulator. A plane coherent light wave illuminates the input. A 1-D FT of g(x) is performed by the cylindrical lens along the x-axis. In the Fourier plane (u,v), a 1-D signal spectrum $G(f_x)$ is displayed along the u-axis and spread along the v-axis. A bank of 1-D filters $H(af_x)$ is placed in the Fourier plane where each of these horizontal strips represents a filter with a different value of the dilation factor "a", which varies along the v-axis. A spherical-cylindrical lens combination performs the IFT along the u-axis and image along the v-axis. The detected output is divided by the factor. The output is a display of the space-translation joint representation of the signal g(x). This is not the only optical implementation of WT. There are a large number of proposed optical systems to perform WT with variable flexibilities.[61]

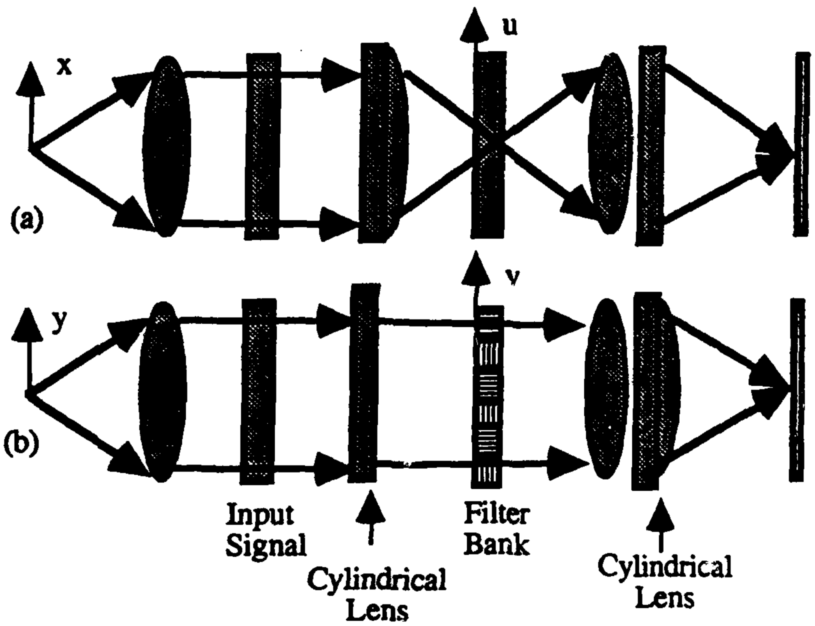


FIGURE 14. OPTICAL WAVELET TRANSFORM PROCESSOR, (A) TOP VIEW, (B) SIDE VIEW[62]

PATTERN RECOGNITION USING WAVELET TRANSFORMS

WTs are proposed to be used in the detection of patterns. Also, WTs are used for noise and clutter suppression. This application is mainly used with classification of targets in cluttered backgrounds. This involves edge detection by wavelet and Gabor functions.[63]

CHAPTER 4
SYSTEM COMPONENTS

In this chapter we present the major components in optical pattern recognition systems. This is presented for review and will not be an extensive or detailed presentation. Both passive and active components will be discussed. These components play a major role in the performance and limitations of pattern recognition systems.

OPTICAL COMPONENTS

The components considered here are passive elements such as FT lenses, beam splitters, and polarizers.

FT Lenses

The basic element in almost all optical systems is the lens, a device that reshapes the wavefronts (equiphase surfaces) of light. Reshaping the wavefront results in deviation of the propagation of light beams. In its simplest form it is made from a material with a different index of refraction from that of the medium surrounding it. There are two types of lenses: convex lenses (thicker at the center than at the edges) which converge plane waves, and concave lenses (thinner at the center than at the edges) which diverge plane waves.

The ideal lens acts as a phase transformer; in other words, it causes a phase change across the light beam passing through it. For a paraxial approximation (rays traveling close to the optical axis) the transfer function, h(x,y), of a spherical lens is given by

$$h(x,y) = e^{-j\frac{2\pi}{\lambda F}(x^2+y^2)}, \tag{13}$$

where λ is the wavelength of the light beam and F is the focal length of the lens.

FT lenses must be chosen with low aberration and high optical quality. The diameter (D) and focal length (F) of these lenses are determined by the overall size of the system, the highest spatial frequency of the object (a) and its maximum length (L), the size of spatial filter (A_f) and the wavelength of the light (λ).

$$D = L + 2\,\lambda aF \tag{14}$$

Polarizing Beam Splitters

Beam splitters are used to split an optical beam. The two emerging beams can have similar or different amplitudes by properly choosing the beam splitter. A second class of beam splitters splits light beams according to their polarizations. Polarizing beam splitters are in the form of a cubic double prism. Light with a certain polarization can propagate through the prism without any reflection while light beams with orthogonal polarization will be reflected. These beam splitters are used in conjunction with spatial light modulators that modulate light by rotating its polarization.

LIGHT SOURCES

For incoherent systems the use of white light sources, such as an arc lamp that is capable of producing enough power for the system, is common. The systems we have considered here are mainly coherent. The coherence length of a laser varies from one type to the other. Gas lasers such as HeNe and Argon, which are widely used in optical pattern recognition, have coherence lengths in the range from a few centimeters to a few meters, while semiconductor lasers, such as AlGaAs, have coherence lengths of about a tenth of a millimeter. Long coherence lengths are required for recording filters in holographic setups. Semiconductor lasers are the favorite for optical pattern recognition systems because of their small size, high power levels and their power conversion efficiency.

DETECTORS

The output from an optical system is usually converted to an electrical signal for post processing. This conversion from optical to electrical power is achieved through a photo detector array. Photodiode arrays are available in many different sizes from a single photo diode to a 1024 x 1024 element array. The size of the photodiode elements in these devices is in the range of 10 mm. A major concern in choosing these devices is that the number of elements should be larger than the space-bandwidth product of the system. This insures no overlapping of the output signals. Thresholding operations can also be performed on the photodiode chip if included in its design. The speed of the photodiode array should be compatible with the speed of the system. It should be as fast as the SLM.

SPATIAL LIGHT MODULATORS

SLMs are optoelectronic devices that are capable of modulating information on an optical beam. SLMs modulate the amplitude, phase, polarization, and/or intensity of the light beam. These devices provide the means for impressing an image on a light beam. SLMs can be either electrically or optically addressed. In the former an electric signal modulates the light beam while in the latter an optical beam provides the modulating signal. SLMs can be static (e.g., photographic film) or dynamic (e.g., liquid crystal devices). SLMs use electro-, magneto-, or acousto-optic effects for modulating the light beam. Chapter 5 provides an expanded discussion of SLMs.

CHAPTER 5

SPATIAL LIGHT MODULATORS

An SLM[64] is a device that can modify the phase, amplitude, intensity, and/or polarization of a one- or two-dimensional light beam as a function of either the intensity distribution of another time-varying modulating optical beam (optically addressed SLM) or a time-varying electrical drive signal (electrically addressed SLM).

SLMs can be either reflective or transmissive. In optically addressed SLMs (O-SLMs) there are two light beams involved--the "write" and "read" beams. These two beams usually have two different wavelengths. In electrically addressed spatial light modulators (E-SLM) there is only one beam that is the "read" beam. In this case the input information (modulating function) is in an electrical format.

Many SLMs take the generic structure depicted in Figure 15. SLMs consist of a charge generating layer and a light modulating layer. In O-SLMs a bias voltage V_b is shunted to the light-modulating material and the charge-generating material (e.g., photoconductor layer). The bias voltage generates an electric field which causes the modulating material to modify the polarization, phase, amplitude, and/or intensity of the readout light beam. The readout beam, shown in Figure 15, passes into the modulating material and is reflected by a mirror at the center of the device. The mirror is usually accompanied by a light-blocking material to prevent the readout beam from leaking into the photosensor. The light modulating layer can be made out of electro-optic crystals, liquid crystals, deformable plastics and other photosensitive materials. In E-SLMs, electric fields are typically applied to the modulating material by electrode matrices, electron beams, or arrays of active transistors.

SLMs perform a wide variety of operations such as multiplications of two functions, amplification of a light beam, conversion from incoherent-to-coherent light, memory or storage of an image, thresholding and other nonlinear operations.

Some other advanced processing functions can be performed by SLMs such as intensity-to-spatial frequency conversion,[65] edge detection[66] and logic operations.[67]

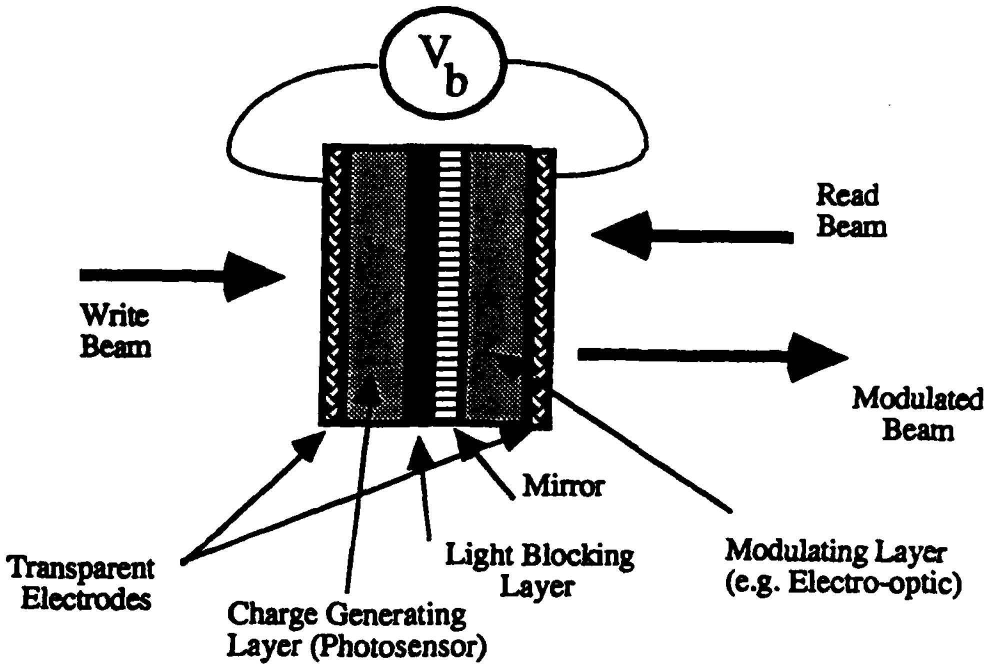


FIGURE 15. BASIC STRUCTURE OF A TWO-DIMENSIONAL SPATIAL LIGHT MODULATOR[64]

SPATIAL LIGHT MODULATOR EVALUATION PARAMETERS

Parameters which characterize SLMs and determine their performance are

1. Responsivity: The ratio between the output to the input beams
2. Useful dynamic range/contrast ratio (number of gray levels)
3. Write and readout wavelength range
4. Cascadability
5. Exposure sensitivity (J/cm^2) for O-SLMs only
6. Framing speed (Hz)
7. Storage time (memory)
8. Spatial resolution (cycles/mm or pix/mm^2)
9. Space bandwidth product (SBW) (total number of pixels)
10. Voltage and power requirements

SPATIAL LIGHT MODULATORS COMPARISON

In Table 1 a comparison is made between the major SLMs listed by the names of their manufacturer. Key parameters are listed in two lists (optically addressed and electrically addressed SLMs). A large number of SLMs are not included such as acousto-optic devices, quantum-well devices, deformable plastics, photorefractive crystals, bistable devices, semiconductor laser arrays and others.

We have listed the main SLMs which are available for use in the market; i.e., those for which sufficient information about their characteristics is available, and those that are commonly used in two-dimensional pattern recognition systems.

TABLE 1. SPATIAL LIGHT MODULATORS COMPARISON

Optically Addressed SLM's ~

Type/ Specifications	Hughes LCLV	Micro-Optics LC	GEC-Marconi LC	Hamamatsu LC	Displaytech FLC	Electron Trapping
Input Window	Fiber-Optic Faceplate	Fiber Optic	Glass	Glass	Glass	Glass
Output Window	Fused Silica	Glass	Glass	Glass	Glass	Glass
Modulation Format	Continuous	Continuous	Continuous	Continuous	Binary	Continuous
Resolution [lp/mm]	20 - 40	30 [*] to 100 [+]	32 - 64	50	20 - 100	40
Response Time	25 - 80 ms	40 ms	20 ms	70 ms	40 ms to 5 ms	1 ms
Contrast Ratio	100:1	100:1	30:1	2π phase	100 to 500:1	
Active Area	25 mm x 25 mm	25 mm x 2 5mm	40 mm x 40 mm	18 mm x 18 mm	27 mm x 27 mm	
Write Light Sensitivity	100 mW/cm^2	100 mW/cm^2	150 mW/cm^2	50 mW/cm^2	45 mW/cm^2	
Write Light Wavelength	430 - 780 nm	488 - 633 nm	430 - 850 nm	430 -700 nm	488 nm (Optimum)	488 nm
Read Light Wavelength	450 - 650 nm	488 - 633 nm	633 nm	633 nm	488 nm	1064 nm
Drive Voltage [peak-to-peak]	1 - 20 V	65 V	5 V Square Wave		45 V	

~ All O-SLMs operate in the reflective mode
[*] Micro-Optics P2010-25
[+] Micro-Optics J2010-33

Electrically Addressed SLMs

Type/ Specfication	Boulder Nonlinear	Display-tech	Texas Inst. DMD	Litton T-MOSLM	Litton R-MOSLM	Hamamatsu EBSLM	Semetex SIGHT MOD	LCTV
Material	Ferro-Electric on VLSI	Ferro-Electric on VLSI	Deformable Mirror	Magneto-Optic	Magneto-Optic	Electro-Optic	Magneto-Optic	Liquid Crystal
Mode	Reflective	Reflective	Reflective	Transmissive	Reflective	Reflective	Transmissive	Transmissive
Modulation Format	Binary Amplitude	Binary Amplitude	Continuous Phase	Binary Amplitude	Binary Amplitude	Continuous Complex	Binary Amplitude	Continuous Amplitude/ Phase
Number of Pixels	128 x 128	128 x 128	128 x 128	128 x 128	128 x 128		48 x 48 256 x 256	120 x 146 [+] to 480 x 640 [*]
Active Area	3.8 mm x 3.8 mm	21 mm x 21 mm	25 mm x 25 mm	18 mm x 18mm	6 mm x 6 mm		25 mm x 25 mm	33 mm x 33 mm [#] 91 mm x 91 mm [*]
Contrast Ratio	10:1	150:1	NA	NA	NA	NA	10,000:1	10:1, [+] 100:1 [*]
Frame Rate [frames/ sec]	5,000	10,000	NA	1,000	10,000	NA	1000	30

[+] Radio Shack 16-155
[*] Sharp XG2000
[#] In-Focus
NA- Not Available

CHAPTER 6

SPATIAL FILTERS

Optical pattern recognition systems discussed in this report mostly employ coherent optical correlators. In these systems, correlation is achieved by IFT, the product of the FT of the signal and reference. The complex conjugate of the reference function is called the spatial filter. Generating the spatial filter is critical to the performance of pattern recognition systems. This chapter discusses the generation of spatial filters both optically and numerically. It also discusses the different filters proposed for improving the performance of recognition systems either by increasing the correlation peak-to-clutter ratio, signal-to-noise ratio, light efficiency or rotation and scale invariance.

CLASSICAL MATCHED FILTER (CMF)

Optical correlators are very powerful for recognizing multiple occurrences of an object in the presence of noise. Let an image be represented by g(x,y) and its two-dimensional FT G(u,v).

$$G(u,v) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x,y)e^{-j2\pi(ux+vy)}\,dx\,dy\,, \tag{15}$$

where u and v denote the spatial frequencies. The objective is to design an optimum linear filter to maximize the ratio of peak signal to mean-square noise. This kind of filter will detect only the image g(x,y). Any other image will result in a smaller correlation peak. This also will be the case if image g(x,y) is slightly altered, e.g., rotation. Also similar images result in similar correlation peaks. This is referred to as a *matched filter*. The transfer function of this filter is shown to be given by[1, 68]

$$H(u,v) = G'(u,v). \tag{16}$$

This filter H(u,v) can be generated optically using holographic techniques shown in Figure 16. The matched filter transfer function H(u,v) is, in general, a complex quantity.

Matched filters can also be displayed on an SLM. In this case the transfer function H'(u,v) needs to be generated numerically.

Matched filters have a number of limitations when used in optical pattern recognition.[69] (1) CMFs are very sensitive to even slight variations in the reference or input images, such as rotation and size change. (2) CMFs are light inefficient because of their transmittance which is much less than unity over many of the spatial frequencies. (3) Most SLMs cannot accommodate the wide dynamic range and complex nature of the transfer function H(u,v). Many different designs have been proposed to overcome some or all of these limitations.

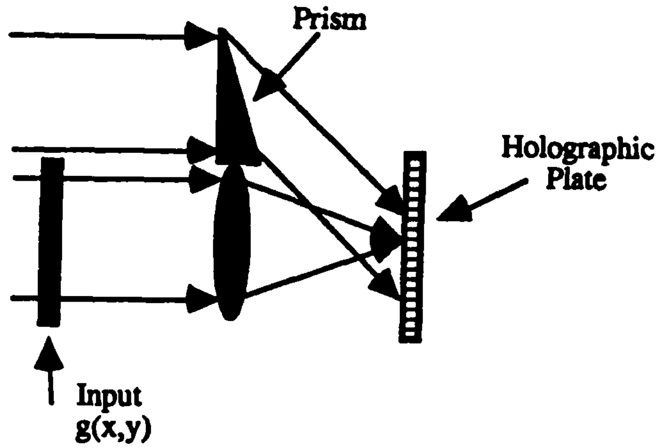


FIGURE 16. HOLOGRAPHIC RECORDING OF A MATCHED FILTER[1]

Phase-only filters (POFs) were proposed[70] to improve the light efficiency because the transmittance of the filter will be unity throughout the frequency spectrum. A binary version of the POFs is called binary phase-only filters (BPOFs).[71] BPOFs were introduced to be implemented using binary spatial light modulators. A large number of composite filters[66] were advanced to achieve multi-object shift-invariant and distortion invariant pattern recognition.

PHASE-ONLY FILTERS

Optimum light efficiency of the matched filter can be achieved through a POF. This filter can be generated by omitting the amplitude information of the matched filter. The transfer function of such POFs becomes

$$H_{PCF}(u,v) = \frac{H(u,v)}{|H(u,v)|} = e^{j\phi(u,v)}, \tag{17}$$

where $\phi(u,v)$ is the phase function of the matched filter. The loss of the amplitude information in the new filter makes it more sensitive to noise. POFs improve the light efficiency of the correlator and also enhance the output peak structure of the correlator. The POF output is similar to a conventional correlation function which is subsequently high-pass filtered.[1,2] In an auto correlation case the output peak is strongly enhanced. This in turn improves the signal-to-noise ratio and the discrimination ability. On the other hand, the POF is more sensitive to distortion variations of the input object such as rotation and scale change.

BINARY PHASE-ONLY FILTERS

The availability of binary SLMs influenced the introduction of the BPOFs. One way of defining the transfer function of the BPOF is

$$H_{BPOF} = \begin{cases} +1, & \text{if } \phi(u,v) \geq 0 \\ -1, & \text{if } \phi(u,v) < 0. \end{cases} \tag{18}$$

The effect of the binarization process is an additional noise term.[74] This noise term can be described as a ghost image. The autocorrelation peak is strongly enhanced over that of the CMF. Also the signal-to noise ratio is improved. The BPOF suffers from the same problem as that of the POF, namely the sensitivity to noise and input function variations.

There are also methods where binarization of the input image was proposed. It has been shown that for some cases the binarization of the input object amplitude resulted in a signal-to-noise ratio compared with gray-scale correlation of the same signals.[75]

COMPOSITE FILTERS

In the previous types of filters, only one view of an object is recorded and the system is capable of recognizing such an object. For practical applications the object must be recognized with all different variations and distortions. Composite filters[76] were proposed for use in optical correlator systems to provide distortion-invariant pattern recognition.

Let $g_1(x,y)$, $g_2(x,y)$, ..., $g_N(x,y)$ denote N training images representing N possible distortions to a reference image g(x,y). Let G(u,v) denote the two-dimensional FT of g(x,y). The objective of the composite filter is to design a filter with a transfer function H(u,v) such that when H(u,v) is placed in the filter plane of an optical correlator we obtain similar output correlation peaks for all input images $g_1(x,y)$, $g_2(x,y)$, ..., and $g_N(x,y)$.

Synthetic discriminant function (SDF)[77] filters were introduced as a way of designing spatial filters that satisfy the above criterion. SDFs are based on the idea of generating the filter through a linear combination of the reference images to create a composite image. The weights for the linear combinations are selected so that the output cross-correlation peaks are the same for all images belonging to one class.[78] The designed filters can be generated using computers or multiple exposure holographic techniques. SDFs are not optimized for noise tolerance. Minimum variance SDFs[79] were proposed to maximize the noise tolerance of the SDFs. The original SDF is designed in such a way that the correlation peak is to be located at the origin. This makes it difficult to determine the location of shifted targets. Minimum average correlation energy (MACE) filters[80] were proposed to solve such a problem. Recently, a new algorithm based on the MACE concept that allows the selection of the spatial frequency content of the filter automatically, has been proposed.[81] This is called an automatic spatial frequency selection algorithm. These filters, given preliminary results, show more tolerance to distortion than the MACE-based correlators. A number of variations of SDFs are described in the excellent tutorial given in Reference 65.

CIRCULAR HARMONIC EXPANSION (CHE) FILTERS

CHEs were first proposed for designing in-plane rotation invariant filters.[82] The input image g(x,y) can be expressed in polar coordinates as g(r,θ). The image g(r,θ) is periodic in θ, with a period of 2π. The image can be expressed as a Fourier series

$$g(r,\theta) = \sum_{m=-\infty}^{\infty} g_m(r)e^{jm\theta}, \tag{19}$$

where $g_m(r)$ is the m[th] circular harmonic component given by

$$g_m(r) = \frac{1}{2\pi}\int_0^{2\pi} g(r,\theta)e^{-jm\theta}d\theta. \tag{20}$$

The filter h(x,y) can also be expressed in terms of its circular harmonics. The cross-correlation between the filter h(r,θ) and input image $g(r,\theta-\theta_o)$, which is the input image rotated by angle q_o, is given by

$$\begin{aligned} C(\theta_o) &= \int_0^{\infty}\int_0^{2\pi} h^*(r,\theta)g(r,\theta-\theta_o)rd\theta dr \\ &= 2\pi \sum_{n=-\infty}^{\infty} q_n e^{-jn\theta}. \end{aligned} \tag{21}$$

where q_n is given by

$$q_n = \int_0^{\infty} rh^*(r)g_n(r)dr. \tag{22}$$

The cross-correlation function $C(\theta_0)$ periodic function in θ_0 the rotation angle of the input. If only one component of the circular harmonics of h(r,θ) is non zero, e.g, $h_{no}(r)$, then q_n is zero for all n except for $n = n_o$. Then the output intensity $|C(\theta_o)|^2$ will be independent of the rotation angle θ_o.

CHAPTER 7

SYSTEM PERFORMANCE AND EVALUATION

This chapter presents system performance and evaluation. The criteria governing performance is introduced first, then system performance comparisons are presented based on these criteria.

PERFORMANCE CRITERIA

Optical pattern recognition systems are used for a wide range of applications. These include character recognition, pattern classification, image enhancement and pattern recognition.

The performance criteria used in this evaluation are based on the discrimination level of the different systems considered. The discrimination level of each system is characterized by

1. sensitivity to noise
2. image distortion (rotation, scaling or translation)
3. the signal-to-noise ratio
4. speed of processing
5. throughput
6. system integration and compactness
7. real-time processing and parallelism

This kind of evaluation requires testing different systems based on similar problems and environment. Since such tests have not been performed, test results are unavailable in the literature.

OPTICAL PATTERN RECOGNITION SYSTEMS COMPARISON

Table 2 is an overall performance comparison that addresses the major parameters with a more or less qualitative evaluation. For a complete comparison a more thorough study needs to be performed.

TABLE 2. OPTICAL PATTERN RECOGNITION SYSTEMS COMPARISON

System	Inco-herent	Coherent				
Parameter	**Cor-relator**	**4-f In-Line**	**Joint-Transform**	**Morphology**	**Neural-Networks**	**Wavelet**
Input SLM	No	Yes	Yes	Yes	Yes	Yes
Coherent Source	No	Yes	Yes	Yes	Yes	Yes
Scale Sensitive	Yes	Mostly Yes	Yes	Yes	Mostly Yes	No
Rotation Sensitive	Yes	Mostly Yes	Yes	Yes	Mostly Yes	Yes
Translation Sensitive	Yes	No	No	Yes	No	No
Off-Line Filter Recording	Yes	Yes	No	Either	Either	Yes
Noise Sensitivity	High	High	High	Medium	Low	Medium
Preprocessing Suitability	No	No	No	Yes	Yes	Yes
Speed	High	High	High	Low (iterative)	Low (iterative)	High
Thresholding	No	No	No	Yes	Yes	No

CHAPTER 8
SUMMARY

State-of-the-art optical pattern recognition systems were reviewed. The problem of recognizing a pattern buried in noise and/or distorted has been addressed. Optics, with its inherent parallelism and speed, is shown to provide the means of constructing a system capable of recognizing and classifying targets with high precision and speed.

Pattern recognition is performed either through template matching or feature extraction. Template matching is performed by comparing the target under inspection with a set of reference images to determine which closely matches the target. Comparing an input image with a set of references can be performed through correlation operations. Feature extraction based pattern recognition is done by detecting particular features in the image. Using a set of measure basis the classification of the image is determined. This classification can be achieved using optical correlators where the reference patterns will be the image features.

Optical systems are capable of performing a correlation operation of a two-dimensional image in parallel. This is made possible by using the FT property of a lens. For an image of 256 x 256 pixels, a coherent optical processor can perform the correlation in 0.6 ns (this is based on 5-cm focal length lenses). Because it is done in parallel, the same time will be required even if the image was 1024 x 1024 or larger; correlation time is the same regardless of the size of the image. This leads to the fact that optical correlators are capable of performing more than 10^9 correlations per second. Electronic processors typically perform less than a hundred correlations per second for a 256 x 256 image. The number of correlations will decrease significantly for larger size arrays. The tremendous computational speed of optical correlators cannot be used by the present technology. SLMs used to modulate light beams with the image are one of the limiting factors in the speed of optical correlators. Ferroelectric SLMs can be operated at 10,000 frames per second, based on a binary SLM.

Optical pattern recognition is performed by direct correlations and determining the correlation peak, or by using nonlinear processing techniques as in the case of morphological and NNs processors. Morphological processing is based on fundamental operations, namely dilation and erosions. These are used in image enhancement such as noise suppression and removal, and image segmentation. Pattern recognition in morphological processing is done using the hit-or-miss transform which can be implemented using optical correlators. Optical NNs are a new means of achieving massive connectivity to perform pattern recognition. This is achieved by the natural parallelism of optics. Neural nets can be trained to recognize a reference set of images. Examples of the application of NNs are associative memory and winner-take-all processors. WTs recently have been introduced as multiresolution processing tools. Optical implementations of wavelets are realized by a coherent optical processor.

Fundamental issues confront both electrical and optical pattern recognition systems. These issues include the recognition of partial or distorted images caused by rotation, scale, translation, or noise. Since it is impossible to store all possible views of an image in a template, a variety of techniques were invented to overcome this problem. This is achieved through creative designs of filters such as, composite filters in the form of synthetic discriminant functions and others. More research is being conducted in designing filters that can be implemented using available spatial light modulators. However, questions still need to be answered concerning the number of reference images needed in recording such composite filters and how to minimize the number of reference images.

Morphological processors can be used effectively in pattern recognition using the hit-or-miss transform. Optical processors can implement such operations with high throughput. The critical operation in these systems is the thresholding operation. Thresholding can be performed by an SLM or other optoelectronic devices such as photodetector arrays. This operation is generally the limiting factor in system throughput.

NNs can be used for recognition or pre- and post-processing operations in conjunction with optical correlators and morphological processors. Optical NNs have been demonstrated to be effective pattern recognition systems.

WTs provide new means for image processing. These transforms can be used in preprocessing operations for noise and clutter suppression as well as in pattern recognition. Optical systems can implement WTs very effectively. These transforms are not sensitive to translation or scale variations.

SLMs are the critical components in optical processing systems. Speed of processing is limited by the speed of SLMs. The available SLMs with high frame rate are mainly binary. The need for analog SLMs is critical for some applications. There is a thrust in industry to develop such devices with a large number of pixels, high speed, and large dynamic ranges.

Optics has great potential for image recognition at extremely high data rates. More research and development are needed in SLMS, high-speed photodiode arrays and thresholding devices. In particular, gray-level SLM development must be actively encouraged. The gray levels required for pattern recognition also must be investigated. Invariant-filter designs for correlator applications need to be studied and developed to achieve a number of objectives. First, filter designs need to be optimized for reference storage. Second, filters suitable for implementation using existing SLMs with limited dynamic range must be developed. System architectures also require research to improve integratability, ruggedness, compactness and power efficiency.

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